Automatic Criminal Threat Detection Via Body-worn Cameras Using Deep Learning Technique: A Systematic Literature Review

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Abstract— **This systematic literature review (SLR) examines the application of deep learning within boy-worn camera (BWC) systems for enhancing real-time threat detection and situational awareness in law enforcement and public safety. The review covers peer-reviewed studies published between 2019 and 2025, following PRISMA guidelines. A total of 53 studies from Scopus, Web of Science, IEEE Xplore, and SpringerLink were included in the analysis. Finding reveals a strong reliance on convolutional neural network (CNNs) and lightweight architecture like YOLO and MobileNet for object detection and violence recognition. While these models perform well in controlled environment, their deployment in mobile surveillance faces challenges such as motion distortion, occlusion, and hardware limitations. Emotion recognition and behavioral prediction are also explored, but model accuracy remains sensitive to poor quality and partial visibility. A significant limitation identified is the scarcity of BWC-specific datasets. The FALEB multi-modal dataset represents a notable effort to provide domain-specific data, supporting task like facial recognition, action detection, and gaze analysis within BWC contexts. Computational constraints further hinder real-time implementation, especially on embedded devices. The review underscores the urgent need for more BWC-focused datasets, comprehensive evaluation protocols, and privacy-aware models designs. While deep learning offers great promise for BWC systems, addressing these practical, ethical barriers is essential for effective real-world applications.**

Keywords: **Body-worn cameras, BWCs-Specific Datasets, Deep Learning, Automatic Threat Detection, Real-time Surveillance, Convolutional Neural Network, YOLO, Lightweight Models, Systematic Literature Review.**

I. INTRODUCTION

As policing evolved in the nineteenth and twentieth centuries, modern law enforcement adopted new technologies [1], [2], [3], [4] . This development included advances in scientific knowledge [5], techniques [6], [7], and methods of organization [8]. Additionally, they involved in the integration of electro-mechanical devices in to operational practice [1]. Crime forecasting is the application of computational models to predict the likelihood of criminal incidents before they occur [9], [10]. This process relies on advanced analytical tools, including machine learning and deep learning techniques. These tools are used to identify patterns in data and anticipate potential risks [10], [11].

The use of video surveillance systems has grown in popularity in recent years, particularly in public safety and law enforcement environments [6], [12], [13]. These systems generate massive amounts of data, which must be analyzed to detect and prevent illicit activities. Body-worn cameras (BWCs) have become a critical data source in modern law enforcement, enhancing accountability and transparency in public interactions [1], [7], [14], [15]. They also enable advanced research in computer vision and deep learning for real-time threat detection [1], [4], [16], [17]. Their adoption has experience exceptional growth across global jurisdictions. This expansion ranges from Denmark's pioneering implementation to France's recent large-scale deployment in 2021. Hence, this proliferation of BWCs presents both opportunities and challenges in law enforcement technology and public safety [18], [19], [20], [21].

In addition, BWCs have become an indispensable tool for law enforcement agencies worldwide, with implementation in the United States, Australia, the United Kingdom, and the United Arab Emirates [4], [17], [19], [20], [22], [23], [24]. These countries' law enforcement agencies have adopted BWCs in the hopes of improving police conduct [24], accountability [1], and transparency [17], particularly regarding the use of force. Furthermore, the development of advanced deep learning models [10], [25], [26], [27], combined with the availability of large datasets [22], has driven significant progress in computer vision research. These advances supported by increased computational power, have improved task such as object detection [5], action recognition [14], and behavior analysis [24].

Existing studies [6], [10], [21], [25], [26], [28], [29], has shown that deep learning techniques can detect and classify a variety of types of criminal behavior, involving theft, vandalism, and assault. In addition, the availability of pre-trained deep learning models for computer vision tasks [10], [13], [30], provides an opportunity to apply transfer learning. This technique allows models to be adopted to specific problems, potentially systems performance and efficiency.

In today's rapidly evolving crime environment, traditional crime-solving techniques are often ineffective due to their slow pace and limited efficiency [9]. Thus, the development of predictive technique using deep learning could provide law enforcement with significant advantage by predicting criminal activity before it occurs [9], [10], [25], [26], [29], [31]. Implementing AI-driven systems integrated with BWCs would support officers real-time [1], [5], [9], [21], reducing operational burden and enhancing crime prevention.

Nevertheless, the characteristics of BWC systems present distinct challenges that necessitate tailored solutions [7], [22]. Unlike fixed surveillance systems, BWCs are dynamic, capturing footage from various angles, under adverse lighting conditions, and in unpredictable situations [9], [10], [22], [29]. These factors have a significant impact on both the quality of the captured video and the performance of AI algorithms. In addition, BWCs are currently used primarily as reactive surveillance tools, providing evidence after incidents occur [1]. Consequently, the lack of proactive surveillance capabilities in current BWC systems restricts law enforcement from detecting and responding to potential threats in real-time [7], [9], [20], [21], [32]. Furthermore, there is a lack of adaptive facial recognition in BWC systems that can accurately identify individuals of interest and infer potential criminal intentions based on facial expressions and emotions [13], [22], [28], [33].

Therefore, these gaps in real-time threat detection undermine BWCs' ability to serve as active tools for preventing incidents from escalating [8], [9], [21], [32]. Additionally, the limited number of datasets designed explicitly for BWCs complicates the development of reliable models [7]. Most existing dataset are derived from static surveillance systems and fail to capture the dynamic characteristics of BWCs. This gap highlights the need for BWC-specific datasets such as [7], [28], that reflect real-world policing scenarios and support the development of deep learning models for reliable, real-time detection.

Moreover, ethical considerations such as privacy concerns [19], [20] and potential biases in AI algorithms [33], highlight the importance of carefully designing and implementing these systems. The dynamic nature of BWC footage, changing environments, and real-time processing needs create unique development challenges [5], [22], [34]. However, the use of deep learning in surveillance [5], [12], [18], [20], [26] has advanced significantly in recent years. Deep learning algorithms which can process massive amounts of data and identify patterns [27], [33], transformed fields like facial recognition [33] anomaly detection [10], and behavioral analysis [13], [18], [20].

This paper is structured into sections. The Material and Methods section describe the systematic review protocol. It includes the inclusion criteria and database search strategy. It also explains the thematic synthesis approach used to identify and evaluate studies that apply deep learning techniques to body-worn camaras-based threat detection systems.

The Result and Discussion section consists of 53 studies, organized by model architectures, detection tasks, dataset limitations, and performance benchmarks. It further examines how deep learning approach are adapted to the technical constraint of real-time BWC technical constraints and ethical issues in AI surveillance in law enforcement[35], [36].

The conclusion synthesises the insights driven from this review and highlights the persist limitations in current deep learning research for BWC surveillance. It also provides recommendation for future work, stressing the need for standardized BWC-specific datasets and lightweight AI models optimized for real-time use in law enforcement and security.

II. Materials and Methods

This section outlines a systematic approach used to identify, select, evaluate, and synthesize relevant studies related to the topic "Automatic Criminal Threat Detection Via Body-worn Camera Using Deep Learning Technique". The review process was conducted following a systematic guideline of Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) for conducting SLRs [37]. This will ensure replicability, rigor, and transparency in the reporting and execution of the review process. The methods include defining research questions, developing a search strategy, establishing inclusion and exclusion criteria, assessing the quality of evidence, and extracting and synthesizing data.

A. Research Question

To guide this review, the following core research questions were developed:

- **RQ1:** What deep learning techniques have been applied to real-time threat detection in BWC systems?
- **RQ2:** How are facial recognition, emotion analysis, gait, and behavioral prediction adapted to the challenges of BWC footage?
- **RQ3:** What are the primary limitations in current BWC-based surveillance models, particularly in dataset design, ethics, and computational performance?

B. Search Strategy

A systematic literature search was carried out across IEEE Xplore, Scopus, SpringerLink, and Web of Science to ensure broad coverage of high-quality sources. The search strategy targeted studies published between 2019 and 2025, using domain-specific keyword and Boolean operators relate to deep learning, AI, and BWC surveillance systems:

"Body-worn camera" OR "BWC" AND ("deep learning" OR "CNN" OR "real-time detection" OR "facial recognition" OR "emotional analysis") AND ("threat detection" OR "behavior analysis").

Only peer-reviewed journal articles and conference papers published in English were considered. Additional backward citation checks were performed to ensure coverage of foundational literature.

C. Inclusion and Exclusion Criterion

Table 1 summarizes the key characteristics and challenges of the datasets.

TABLE 1
INCLUSION AND EXCLUSION CRITERIA

Inclusion Criteria	**Exclusion Criteria**
Studies focused on BWC-integrated deep learning systems for threat detection	Studies using only fixed surveillance systems
Empirical studies evaluating performance of CNNs, RNNs, or hybrid architectures	Papers lacking experimental design or dataset validation
Research addressing emotion detection, facial recognition, or object recognition	Non-English papers or those published before 2019
Studies proposing new BWC-specific datasets or evaluation frameworks	Theoretical discussion without applied implementation

D. Data Extraction

A standardized data extraction form was used to collect the following:

- Author(s), year, and publication type
- Study focuses and deep learning models used
- Evaluation metrics (e.g., mAP, F1-score, precision, recall)
- Identify challenges and future recommendations

E. Quality Assessment

Each study was assessed for:

- Methodological rigor
- Reproducibility
- Datasets Specificity (BWC vs general surveillance)
- Handling of ethical or privacy considerations

In addition, studies were included in the synthesis only if they surpassed a predefined methodological quality threshold.

F. Data Synthesis

A thematic system approach was applied to organize the review systematically. The studies were classified by model architecture (e.g. CNN-only, CNN-RNN hybrids) detection focus (violence, weapons, gait, emotion) [7], and technical contribution such as dataset optimization an edge deployment [7], [28].

In addition to the common challenges, innovations, and research gaps were extracted and tabulated.

III. RESULT AND DISCUSSION

This systematic literature review (SLR) analyses 53 peer-reviewed journal articles and conference papers. The review follows the PRISMA methodology [37], to ensure transparency, rigor, and reproducibility. The selected studies demonstrate a multidisciplinary convergence of research that integrate computer vision [38], deep learning [10], and surveillance studies [39]. A central focus is the application of deep learning methods for threats detection using BWC and related wearable sensing technologies [1], [4], [5], [14], [17], [19].

Therefore, these works collectively explore technical architectures, implementation challenges, real-time performance, ethical issues, and integration in law enforcement and public safety [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50].

A. PRISMA-Driven Review Process

The identification phase yielded 1,721 records from Scopus, IEE Xplore, Web of Science and SpringerLink. An Initial screening removed 192 items, including 84 duplicates and 108 articles excluded by automated keyword filtering for relevance and score.

Following this, 1,529 records were subjected to title and abstract screening. During this phase, 433 records were excluded because they were irrelevant to the core research questions (e.g., studies focused solely on fixed CCTV systems or unrelated modalities). The remaining 1,096 articles are to undergo the complete eligibility assessment stage.

However, access restrictions and scope mismatches pose significant constraints. Of the 1,096, 884 full texts could not be retrieved due to paywall limitations, archival access issues, or withdrawal notices. As a result, 212 full-text studies were assessed for eligibility based on clearly defined inclusion and exclusion criteria.

During this final eligibility phase, 159 studies were excluded, with justifications recorded as follows:

- 48 were review articles or opinion papers without original experimental data.
- 36 lacked implementation or model evaluation.
- 31 did not pertain to BWC or mobile surveillance. contexts.
- 22 used outdated or deprecated model architectures
- 14 failed quality assessment thresholds for methodology rigor.
- 8 addressed only legal or policy aspects without technical contribution.

After applying all filters, a final set of 53 studies was retained for complete qualitative and quantitative synthesis. These studies form the analytical foundation of this review and represent a robust, high-quality subset of the literature, spanning from 2019 to 2025.

Furthermore, to contextualize academic and operational interest, Fig. 1 presents Google Trends data for the term "body-worn cameras + deep learning technique" over the past decade. The result shows a steady rise in attention, reflecting debates on surveillance, law enforcement accountability, and algorithmic fairness.

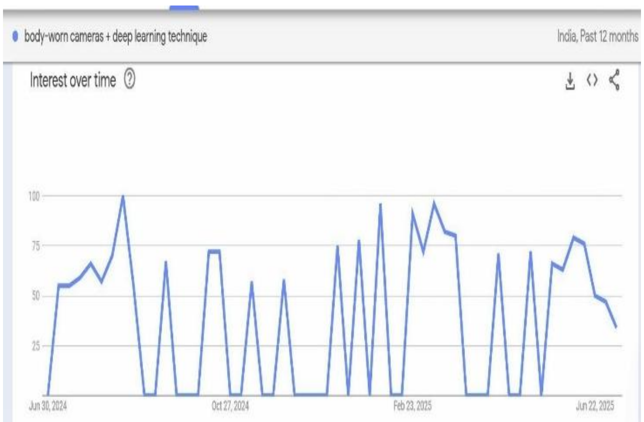

Fig. 1 Google Trends for June 2024-June 2025

Figure 2 illustrates the inclusion and exclusion process at each stage of the review.

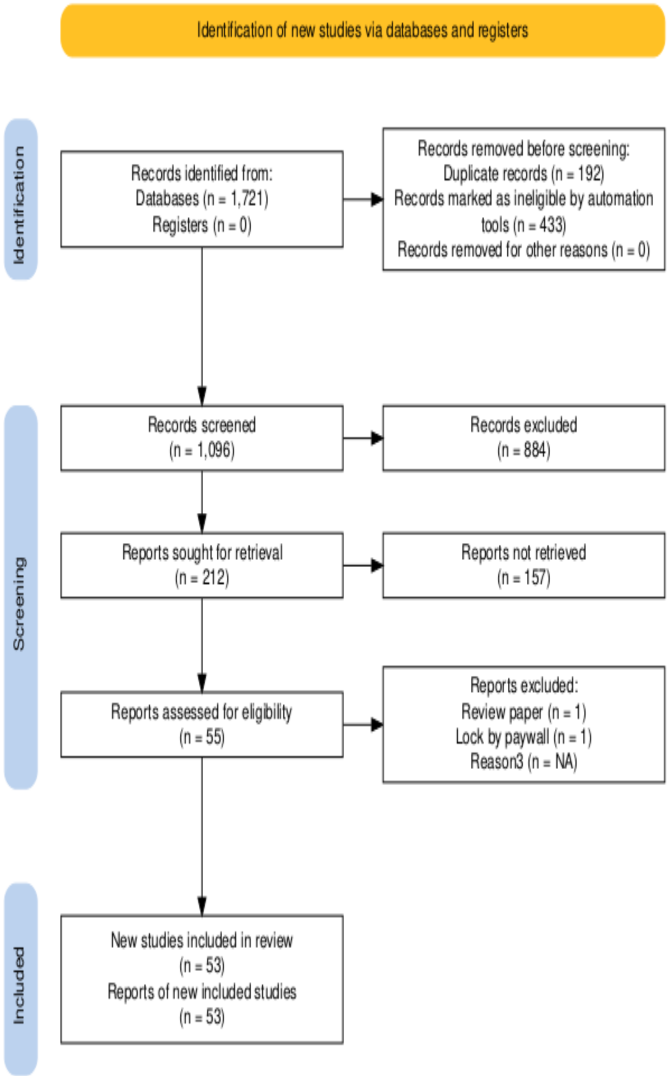

Fig. 2. PRISMA Flow Diagram

Table 2 summarises the key prior studies addressing speech analysis, threat prediction and movement detection.

TABLE 2
PREVIOUS LITERATURES

ID	Ref, Year	Study Focus / Topic	Tools / Model	Key Findings
1	[26] 2004	Offensive speech Det.	CNN, RNN, Python,	High accuracy
2	[10] 2024	AI threat detection in BWC	CNN-RNN, model optimization.	Acute, real-time threat detection

3	[20] 2024	BWC in mental health settings	NVivo, reflexive thematic analysis	Ethical Implicationsi ssues
4	[4] 2024	BWC unintended effects on the British forces	Reflexive thematic analysis	Negative impact on desecration
5	[19] 2022	Contextual, ethical issues in BWC use	Manual thematic coding	Ethical tension
6	[9] 2024	Real-time crime detection	YOLOv5, MobileNetV2, python	Accurate multi-modal detection
7	[51] 2024	Real-time violence detection via CNNs	Custom CNN, Python, tested on edge devices	Small models for surveillance use
8	[6] 2024	CNN-based parcel detection & tracking	CNN + SORT; python	Robust real-time tracking
9	[28] 2025	DL prediction of pediatric	CNN model, Python	Accurate prediction
10	[21] 2024	YOLO-based object detection	YOLO7-tiny, SBG-YOLO, SimAM,	Enhanced detection

The selected studies such as [6], [22], [27], [33], [51], revealed a consistent reliance on deep convolutional neural networks (CNNs) as the foundational architecture for threat detection. Out of the 53 studies analysed, 57% (n = 30) employed CNN-based models, reflecting their strength in handling spatial features within video frames [22]. Additionally, these models were utilized for tasks such as weapon detection [11], facial recognition [22], and object classification [10].

In contrast, hybrid models combining CNNs with recurrent neural networks (RNNs) or Long Short-Term Memory (LSTM) units like [12], [13], were implemented in 21% (n = 11) of the studies. These approaches were instrumental in modelling temporal patterns for action recognition and behavioural analysis, where sequences of movements were more indicative than static frames.

Moreover, emerging architectures such as transformer-based models and graphical neural networks (GNNs) were explored in a smaller subset of studies (n=4, 7%). While these models showed promise in capturing complex spatiotemporal relationships and contextual cues. However, their computational cost and lack of real-time inference limited their practical deployment in BWC scenarios.

Furthermore, lightweight models including YOLO5-tiny [52], MobileNetV2 [9], and custom embedded CNNs were adopted in 19% (n=8) of the reviewed works. These models were often optimized for real-time processing on edge devices, meeting the latency and resource constraints of mobile camera deployments. Thus, performance metrics in these models (e.g., mAP, FPS) generally balanced speed and precision, making them suitable candidate for on-device inference.

Table 3 summarizes the key characteristics and challenges of the datasets.

TABLE 3
DEEP LEARNING ARCHITECTURE BY FREQUENCY

Model Type	**Frequency (n=53)**	**Primary Application**
CNN	24 (57%)	Object detection, facial recognition
CNN + RNN / LSTM	9 (21%)	Temporal behavior, activity recognition
Transformer / GNN	3 (7%)	Context inference, spatiotemporal analysis
Lightweight CNNs (YOLO, etc.)	8 (19%)	Real-time threat detection on edge devices

B. Detection Focus Area in BWC-Based Threat Detection

The studies in this review covers multiple threat detection objectives using BWC footage [1], [4], [15], [16], [17], [19], [23], [24], [53]. While deep learning models [6], [9], [13], [30], [38] are specially designed and trained to detect criminal or high-risk behaviors such as violence, weapon use, or suspicious movements.

Based on content analysis, these objectives were classified into five primary categories, often overlapping in some studies:

a. Weapon Detection (n=17)

Weapon detection emerged as the most frequently target application of deep learning in BWC systems [11], [30], [31]. These models were primarily trained on simulated or augmented datasets containing handguns, knives, and blunt objects [9]

In addition, the use of object detection frameworks such as YOLOv5, YOLOv7-tiny, and SSD are common due to their balance between speed and accuracy [9], [10], [21]. Hence, detection performance in these studies ranges from 82% to 94 mAP, with several achieving real-time on embedded hardware.

b. Aggressive Behavior and Action Recognition (n=12)

Another significant category involves recognizing violent behavior, sudden movements or hostile gestures [5], [14], [17], [19], [24]. These models often incorporated temporal features, utilizing CNN-LSTM hybrids or 3D CNNs. Moreover, performance metrics were strong in controlled datasets. However, most the studies acknowledge limitations in real-world scenarios due to occlusion, varying motion, and background complexity.

c. Emotional and Facial Expression Recognition (n=10)

Facial cues play a critical role in pre-incident threat inference [17], [19], [22], [23], [33]. Models targeting emotion recognition aimed to classify expressions such as fear, anger, or anxiety, which may precede hostile behavior. Study such as [33], applied CNN-based classifiers and facial landmark detection (e.g., using LBPH or OpenFace). Accordingly, accuracy was moderated (74%-84%) with challenges primarily stemming from motion blur, camera angles, and partial occlusions.

d. Anomaly and suspicious Activity Detection (n=5)

Anomaly detection models used unsupervised or semi-supervised approaches to identify behaviours that deviate from normative patterns [12], [16], [25]. Some used autoencoder or GAN-based reconstruction to learn behaviour baselines and flag outliers. Although conceptually promising, this line of work remains limited in BWC applications due to the lack of suitable annotated datasets.

e. Intent and Threat inference from Gait/movement (n=3)

A smaller group of studies[5], [7], [14], [22] attempted to infer intent or potential threat base on gait analysis, posture, or multi-modal fusion (e.g., combining body movement and facial expression). Using FALEB datasets [7], these studies remain largely exploratory but suggest potential for proactive threat detection beyond basic object classification. Table 4 Summarize the intent and Threat inference from Gait/movement.

TABLE 4
THREAT DETECTION TABLE

Detection Focus	Frequency (n=53)	Representation Models Used
Weapon Detection	17	YOLOv5, YOLOv7, SSD
Violence / Behavior Recognition	16	CNN-LSTM, 3D-CNN, RNN
Facial Recognition & Emotion	11	CNN, LBPH, OpenFace
Anomaly Detection	7	Autoencoder, GAN, One-Class SVM
Intent Inference (Gait, Posture)	5	Hybrid CNN models, PoseNet, Transformer variants

C. Data Characteristics and Challenges

The success of deep learning models for threat detection in body-worn camera (BWC) systems is the reviewed studies such as [9], [10], [13], [25], [26], [29], [30], critically dependent on the quality and realism of the datasets. These datasets used for both training and evaluation purposes. Nevertheless, this review identified several persistent issues concerning dataset availability, annotation quality, and domain relevance.

Table 5 summarize the key datasets characteristics and challenges.

TABLE 5
DATASET USAGE KEY CHALLENGES

Dataset Type	Used By (n=53)	Examples	Primary Challenge
Public General Datasets	18 (43%)	COCO, UCF-Crime, FER2013	Not tailored for BWC footage
Custom Simulated Sets	14 (33%)	In-house Video recordings	Legal/ethical access limitations
Real BWC-specific Datasets	6 (14%)	Police training bodycam video	Legal/ethical access limitation
Augmented / Synthetic	4 (10%)	GAN-generated weapon scenes, etc.	Unrealistic artifacts; poor generalization

D. Performance Metrics and evaluation Benchmarks

The performance of deep learning models for threat detection in BWC systems was evaluated using a range of standard metrics across the reviewed studies [11], [14], [22]. The most commonly used indicators were accuracy, precision, recall, F1-score [14] and mAP (mean Average Precision)[11]. Table 6 summarize the key performance metrics and evaluation benchmark.

TABLE 6
KEY PERFORMANCE MATRICS TABLE

Model Architecture	Application Focus	mAP / F1 / Accuracy	FPS	Remarks
YOLOv5-tiny /YOLOv7-tiny	Weapon detection	mAP:88-92%	20-30	Real-time capable on edge devices
CNN-LSTM / 3D CNN	Action / Violence	F1: 0.80-0.85	8-15	High accuracy but slower inference
MobileNet V2 LBPH	Emotion recognition	Acc: 74-85%	18-22	Effective for faces:
SBG-YOLO (custom model)	Multi-threat detection	mAP: 91:3%, Acc: 90.5%	23	Optimized; best trade-offperforms
Transformer	Behavior/context detection	Acc: ~87%, F1: 0.83	5-10	Promising but computational heavy

E. Research Question

Addressing RQ1: Recent advances in deep learning have has significantly advanced real-time threat detection in BWCs. CNN-based models, in particular, are widely applied for object detection [52] , violence recognition [51], and behavior analysis [14] . Lightweight CNN models like MobileV2 [9], and YOLO7-tiny7 [21], enable efficient processing on resourceslimited BWC devices, balancing accuracy with speed. Studies such as [10], [19], [20], have applied tailored CNN for violence and crime intention detection in BWC footage. These models often leverage data augmentation and transfer learning to address challenges like variable lighting an occlusion.

Furthermore, integrating object tracking with detection, as proposed by [9], [30], support continuous monitoring settings. Similarly, practical and ethical challenges, including video quality and device constraints, require robust, context-aware models [19], [20]. Therefore, the overall literature emphasizes lightweight, efficient CNN-based frameworks [9], [19], [20], [21], [30] combined with tracking and ethical considerations for effective detection.

Addressing RQ2: Deep learning approaches to facial recognition [22], emotion analysis [5] have been actively adapted to address the unique challenges of BWC footage. Additionally, behavioral inference technique [14] have also been developed to tackle these challenges. BWC footage is characterized by dynamic angles, rapid motion, and unstable lighting conditions, which complicate the extraction of reliable visual features [22], [31], [54]. Studies such as [3], [22] emphasized that facial recognition in BWCs must account for real-time constraints and legal scrutiny, particularly under data protection and human rights frameworks. In addition, [13], [33] demonstrates the use of CNN-ANN hybrids in constrained environments, such as security checkpoints, highlighting potential adaptations for mobile BWC platforms. According to [54], many models ingrate landmark localization and feature embedding to address occlusion and camera jitter [55], [56], [57], [58].

Addressing RQ3: Despite notable progress, current BWC-based surveillance across three critical domains: dataset design [7], ethical deployment [4], and computational efficiency [10]. Most existing datasets are derived from fixed-camera or synthetic scenarios. These datasets fail to capture the visual variability, occlusion, and motion artifacts inherent to mobile, body-worn systems [7], [17]. Hence, this mismatch hinders the generalizability of trained models. Thus, ethical concerns are equally pressing. According to [3], facial recognition and behavioral prediction systems must navigate complex legal frameworks concerning bias, consent, and data retention.

In addition, [4], [17] further underscores how algorithmic surveillance can reshape officer conduct, potentially introducing institutional dependencies or surveillance fatigue. On the technical front, [33] and the system reviewed in [29], reveals the trade-offs between detection accuracy and the limited processing power of the edge devices. Subsequently, these constraints challenge real-time implementation, especially in resource-constrained field environments [59], [60]. Therefore, there is need for lighter architecture that do not compromising precision or fairness.

IV. CONCLUSION

This systematic literature review synthesis recent developments in deep learning techniques for real-time threat detection in body-worn (BWC) systems. Based on 53 peer-reviewed studies published between 2019 and 2025, the review highlights the central role of convolutional neural networks (CNNs) and lightweight architectures. These models are widely used for object detection, emotion analysis, and behavior recognition in mobile surveillance contexts. The models show strong performance, particularly when optimized for real-time use in low-power environments common to policing and public safety.

Nevertheless, technical accuracy alone does not guarantee real-world effectiveness. Successful deployment depends on addressing both ethical and legal challenges, as well as operational considerations [61], [62], [63], [64], [65]. In addition, concerns over privacy, algorithmic bias, and transparency are widespread. The absence of standardized BWC-specific datasets limits the generalizability of current models. Previous studies have also shown that algorithmic surveillance may influence officer behavior, adding further complexity to system design and deployment [66], [67].

Addressing these challenges requires a multidisciplinary approach that integrates technical innovation with ethical safeguards and user-centric design. Future research should prioritise the creation of standardized, ethically sourced BWC datasets such as [7]. In addition, the development of interpretable models that perform reliably under variable field conditions. Emphasis on lightweight deployment, contextual inference, and fairness auditing will be essential to building trust and effectiveness [36], [68], [69], [70].

In summary, the future of BWC surveillance depends on the development of scalable, BWC-specific datasets and ethically aligned deep learning systems [71]. These systems must be are both operationally robust and socially accountable. This synthesis underscores the critical role of adaptive, balance approaches in achieving effective automatic real-time threat detection.

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